Macro factors and the realized volatility of commodities: A dynamic network analysis

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A B S T R A C T

This paper explores the relationship between macro-factors and the realized volatility of commodity futures. Three main commodities—soybeans, gold and crude oil—are investigated using high-frequency data. For macro factors, we select six indicators including economic policy uncertainty (EPU), the economic surprise index (ESI), default spread (DEF), the investor sentiment index (SI), the volatility index (VIX), and the geopolitical risk index (GPR). These indicators represent three dimensions from macroeconomics and capital markets to a broader geopolitical dimension. Through establishing a dynamic connectedness network, we show how these macro factors contribute to the volatility fluctuations in commodity markets. The results demonstrate clearly distinctive features in the reaction to macro shocks across different commodities. Crude oil and gold, for example, are more reactive to market sentiment, whereas DEF contributes the most to the realized volatility of soybeans. Macro-economic factors and geopolitical risks are more relevant to crude oil volatilities compare to the other two. Our empirical results also reveal the fact that the macro influence on the realized volatility of commodities is time varying.

1. Introduction

Commodity futures has become increasingly popular as a financial instrument to hedge against risks in financial markets. Its further integration into the global financial system is strengthened due to the financialization process in commodity markets (Zhang and Ji, 2019). According to Tang and Xiong (2012), the total value of the market transactions of institutional investors increases on a large scale, and a large amount of funds flow into commodity market, giving commodity prices clearly new features. Traditionally, commodity prices are determined by global imbalances of demand and supply (Wu et al., 2020). The recent trend, especially after the 2008 global financial crisis, has revealed a very different scenario. Extreme price dynamics, higher short-term volatility, and increasing level of co-movement in commodity prices are far beyond the explanatory power of the standard demand and supply framework . As a consequence, factors that may affect commodity price movement have becoming more complicated.

In the financialization process, investors in commodity market are more vulnerable to nonconventional shocks such as market sentiments, policy uncertainties and other unexpected events. For example, with a large number of investors entering commodity futures market in the recent years, market friction and investor sentiment have caused dramatic fluctuations in commodity prices, which also lead to deviations between commodity prices and economic fundamentals (Masters, 2008; Tang and Xiong, 2012). At the same time, monetary policies, business cycles and other macroeconomic information remain influential. Global economic uncertainties and rising systemic risks in the international financial system have also spill over to commodity markets.

Taking financialization and a broad category of factors (other than traditional supply and demand) into commodity pricing models has become a booming research direction (Ji et al., 2019). A major focus among scholars is to discover the underlying mechanisms of how these factors may affect commodity prices, and then how to accurately measure the impacts. Studies have separately investigated the driving factors behind commodity prices from the perspectives of supply-demand and macroeconomic fundamentals (Trostle, 2008; Akram, 2009; Matesanz et al., 2014), uncertainty, geopolitical risk and extreme events (Balcilar et al., 2016; Joëts et al., 2017; Bilgin et al., 2018; Antonakakis et al.,

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2017; Gkillas et al., 2019), and commodity financialization (Deaton and Laroque, 1992, 1996; Masters, 2008; Tang and Xiong, 2012).

In terms of supply-demand and macroeconomic fundamentals, Mackey (1989), Deaton and Laroque (1996), and Chambers and Bailey (1996) find that resource commodity market is usually an oligopoly market, and sellers mostly control the quality and quantity of supply, which has a great influence on commodity pricing. However, Jacks and Stuermer (2020) argue that the impact of commodity supply on commodity prices gradually decreases over time, while demand factors have increased their influence. Trostle (2008), Kilian (2009), and Cevik and Sedik (2011) also suggest that the rapid growth of commodity demand is the main reason for the overall rise in commodity prices. Moreover, Matesanz et al. (2014) find that commodity prices are connected with each other. The reason behind the price linkage is complicated. Baffes (2007) believes that the linkage between agricultural products and fossil energy is the mutual substitution between them. For example, the high price of oil increases the demand for agricultural products as the sources of bioenergy, leading to the increase in agricultural product prices. This logic is also supported by Gohin (2008) and Zhang et al. (2010). In addition, Gleich et al. (2013) examine the impact of non-renewable resources supply factors, economic and demographic factors on commodity prices. They find that most of commodity prices can be explained by fundamental factors. Among them, the world's GDP, mine production and stock-keeping are the top three most important factors. Kagraoka (2016) uses generalized dynamic factor model to study the driving factors of the monthly prices of commodities, and finds that the U.S. inflation rate, the world industrial production, the world stock index and the price of crude oil are four common dynamic factors that determine commodity prices. Bhardwaj et al. (2015) use default spread (DEF) as a proxy of business cycle to explore whether macroeconomic risks will lead to commodity risk premiums, and the results show that there are obvious business cycle components in the correlation between the commodity prices. Batten et al. (2010) also examine the impact of macroeconomic determinants, including business cycles, monetary environment and financial market sentiment, on the monthly price fluctuations of precious metals. They conclude that macroeconomic factors have a spillover effect on precious metal price fluctuations. Recently, some researchers argue that the exchange rate of the US dollar as well as interest rates (Akram, 2009; Gruber and Vigfusson, 2018), economic activity (Klotz et al., 2014) and other macroeconomic factors (Smiech and PapiezaDabrowski, 2015; Zhang et al., 2019) are also important sources to drive commodity price fluctuations.

Entering the new century, extreme events happen more frequently together with a clearly rising geopolitical risks across the world. The global financial crisis in 2008 has changed the global economic condition and raised worldwide economic uncertainties. And then the world has seen the European sovereign debt crisis, the Ukraine-Russia conflict, turmoils in the Middle East, and now the pandemic of coronavirus (Zhang et al., 2020; Ji et al., 2020a). All of these have profound impacts on commodity markets and thus lead to a number of empirical studies. Joëts et al. (2017), for example, examine the impact of macroeconomic uncertainty on commodity prices and volatility. They find that the agricultural and industrial markets are more sensitive to changes in macroeconomic uncertainty, whereas the sensitivity of precious metals markets is relatively low. Balcilar et al. (2016) use a nonparametric causality-in-quantiles test to examine the relationship between various uncertainty measures and gold returns. A causal relationship from uncertainty measures to both gold returns and volatility is found. Bilgin et al. (2018) explore the impact of the volatility index (VIX), skewness (SKEW), global economic policy uncertainty (EPU), and the partisan conflict indexes (PC) on gold prices. Their results show that gold prices exhibit a positive response to negative changes in the VIX index and positive changes in the EPU index. Prokopczuk et al. (2019) also examine the relationship between economic uncertainty and commodity market volatility. They find that credit risk, financial market stress, and fluctuations in business conditions are important predictors of

commodity market volatility. Antonakakis et al. (2017) and Gkillas et al. (2019) confirm the predictive power of geopolitical risk in crude oil and gold price fluctuations, respectively. Furthermore, some researches, such as Tzeng and Shieh (2016), Vercammen (2020) and Yousef (2020), examine the performance of commodity markets in extreme cases, and find clear differences of commodity markets in normal periods.

Studies on commodity financialization have also found some interesting results. Deaton and Laroque (1992, 1996) show that an influx of speculators in commodity markets will significantly increase the volatility and autocorrelation of commodity prices. Hong and Yogo (2012) develop a simple model to identify the predictive power of open interest in commodity markets. They show that there is a high positive correlation between movements in open interest and commodity prices, and one standard deviation increase in commodity market interest will lead to a 0.73% increase in expected commodity returns per month. Masters (2008), Tang and Xiong (2012) argue that high frequent trading in commodity markets can cause commodity prices deviation from fundamentals. In addition, Bahloul (2018) examines the effect of traders' sentiment on the return of commodity markets, and finds that irrational traders' overreaction to the news leads to abnormal profits in commodity markets. Basu and Miffre (2013) construct factor mimicking portfolios to capture the correlation between commodity futures risk premiums and investor' hedging pressure. Büyükşahin and Robe (2014) study the relationship between commodities and stock returns using a non-public trader position dataset of 17 commodity futures markets, and they suggest that the link between commodities and stock returns grows as the financialization of commodities strengthens. Adams et al. (2020) select four economic variables and four financial variables to explore the impact of financialization on commodity markets at monthly frequency. They show that financial variables have become the main drivers of commodity returns and volatility after commodity financialization. Furthermore, Mensi et al. (2017a,b), Bouri et al. (2017) and Ji et al., 2018a, 2018b examine the dependence structure between energy and agricultural commodity price fluctuations from the perspective of risk management. They find that the existence of risk spillovers from energy to agricultural commodities, and the dependent structure between them is not only time-varying, but also sensitive to time horizons.

Most of the existing literature focuses on a single dimension of factors, while the evidence of commodity financialization shows the importance of financialization and news factors in the commodity market, as well as the multidimensional nature of the problem. These three dimensions discussed above are not necessarily separated from each other, instead, they are intrinsically linked in a complex system. Without synthetically including all dimensions into the analytical framework, empirical results may be biased or partial. To overcome this problem, and extend from these existing knowledge, this paper focus on the aspects of financialization and macro news, explicitly takes all three dimensions into consideration, and empirically investigates how the broad macro factors contribute to fluctuations in commodity markets. Specifically, we use economic policy uncertainty (EPU), the economic surprise index (ESI), default spread (DEF), the investor sentiment index (SI), the volatility index (VIX), and the geopolitical risk index (GPR) to identify the main information transmission channels and drivers that affect commodity price fluctuations, and provide investors and policy-makers with implications of commodity investment or management that respond to rapidly changing macro situation.

This paper also makes the following additional contribution to the literature: first, 5-min high-frequency commodity futures data is used to construct realized volatility. Compare to the use of low-frequency data, this can better capture commodity price volatility. Second, soybeans, gold, and crude oil are selected as the representatives of three major commodity markets, namely, agricultural, metal, and energy products. And these three commodities are the most typical commodities verified in most existing literature. Doing so allows us to compare the typical similarities and differences of macro-volatility linkages among different type of commodities, which can offer valuable information for investors

forming strategies across markets. Third, this paper adopts the connectedness network approach proposed by Diebold and Yilmaz (2014). This approach overcomes the endogeneity problems in time series analysis and is robust to variable ordering, and also allows us to analyze interactions among variables in a systemic way. The network perspective provides an effective way to describe underlying mechanisms from system-wide level to pairwise level, and thus avoids controversial issues related to "contagion" or "herding behaviour". Moreover, a rolling-window extension of the basic results can easily be used to reveal the possible dynamic relationship.

This remaining parts of this paper is structured as follows: section 2 introduces the estimation of realized volatility and also the connectedness network approach proposed by Diebold and Yilmaz (2014). Section 3 explains the data and reports empirical results. The last section concludes.

2. Methodology

2.1. Realized volatility estimation

Andersen and Bollerslev (1998) propose to use high-frequency data to calculate realized volatility (RV) as a proxy for the integrated variance, which is defined as the sum of squared intraday returns. RV can provide more accurate measure of volatility, and thus we use the Andersen and Bollerslev (1998) approach defined as

$$RV_t = \sqrt{\sum_{j=1}^{M} r_{t,j}^2} , \ t = 1, \ldots, T \tag{1}$$

where $r_{t,j} = ln(P_{t,j}/P_{t,j-1})$ represents the intraday logarithmic returns on day t, and $P_{t,j}$ is the price at time j on day t. M is the total number of intraday samples.

The accuracy of RV depends on sampling frequency. A higher sampling frequency can better capture volatility information, but with the increase in sampling frequency, the noise of the market microstructure also increases, which leads to a decrease in the measurement accuracy of the high-frequency RV. Andersen et al. (2001) suggest that 5-min is the optimal sampling interval for a liquid market to balance the advantages of using high-frequency data and the disadvantages of microstructure noises. In practice, 5-min is also the time frequency adopted by most existing literature (Bandi and Russell, 2006; Patton, 2011). Hence, this paper also 5-min high-frequency data to construct the realized volatility.

2.2. Connectedness network

Diebold and Yilmaz's (2014) connectedness network approach is a simple and very powerful method to describe systemic interactions based on the vector autoregressive (VAR) model and the generalized variance decomposition (GVD) method. It has been widely used in the analysis of cross-market risk contagion (Maghyereh et al., 2016; Zhang, 2017; Mensi et al., 2017a,b; Rehman et al., 2018; Ji et al., 2018a, 2018b) and systemic risk analysis (Alter and Beyer, 2014; Diebold and Yilmaz, 2014; Fernando et al., 2016). Compared with traditional measurement approaches (such as cointegration, causality analysis, etc.), this approach can provide more intuitive descriptions of the direction and intensity of information spillovers occurring between multivariable.

First, a VAR(p) model is constructed:

$$y_t^m = \sum_{i=1}^{p} \Phi_i^m y_{t-i}^m + \varepsilon_t^m \tag{2}$$

where y_t^m is an $N \times 1$ vector, including the realized volatilities of commodity m (m = soybeans, gold, and crude oil, respectively) and the macro factors. Φ_i^m is the matrix of autoregressive coefficients, and $\varepsilon_t^{m\sim}$ $(0, \Sigma^m)$ is the vector of random errors. The VAR model can be converted

into the vector moving average (VMA) representation:

$$y_t^m = \sum_{j=1}^{\infty} A_j^m \varepsilon_{t-j}^m \tag{3}$$

where the $N \times N$ matrices A_j^m can be calculated by the recursive formula $A_j^m = \Phi_1^m A_{j-1}^m + \Phi_2^m A_{j-2}^m + \ldots + \Phi_p^m A_{j-p}^m$ $(j = 1, 2, \ldots)$ with $A_0^m = I_N$ and $A_j^m = 0$ for $j < 0$.

After estimating the model, the generalized variance decomposition method proposed by Pesaran and Shin (1998) can be constructed. Equation (4) calculates the H-step ahead generalized forecast error variance decomposition:

$$\theta_{ij}^H = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j \right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i \right)} \tag{4}$$

where θ_{ij}^H measures the variance contribution of the innovations in variable j to variable i at the H-step ahead. e_j is a selection vector with one as its jth entry and zeros elsewhere. A_h is the h-lagged coefficient matrix in the moving-average representation of the VAR model. Σ^m is the covariance matrix of the error vector in the VAR model, and σ_{jj} is the jth diagonal entry of Σ. Due to the non-orthogonalized shocks in the GVD environment, the row sums of the generalized forecast error variance decomposition matrix are not unity in general. Hence, we normalize equation (4) as the following function to ensure the row sum equals one:

$$\tilde{\theta}_{ij}^H = \frac{\theta_{ij}^H}{\sum_{j=1}^{N} \theta_{ij}^H} \tag{5}$$

The generalized variance decomposition matrix can be constructued as $\tilde{\theta}^H = [\tilde{\theta}_{ij}^H]$, and $\sum_{j=1}^{N} \tilde{\theta}_{ij}^H = 1$. Diebold and Yilmaz (2014) further propose several connectedness measures and construct the connectedness network.

Given that the pairwise directional connectedness from j to i is $\tilde{\theta}_{ij}^H$, then the net pairwise directional connectedness between i and j can be written as

$$C_{ij}^H = \tilde{\theta}_{ij}^H - \tilde{\theta}_{ji}^H \tag{6}$$

Then, the total directional connectedness from others to i (From) and the total directional connectedness to others from i (To) are defined as

$$C_{i\leftarrow .}^H = \sum_{j=1, j/=i}^{N} \tilde{\theta}_{ij}^H \tag{7}$$

$$C_{.\leftarrow i}^H = \sum_{j=1, i/=j}^{N} \tilde{\theta}_{ji}^H \tag{8}$$

In order to measure the net information spillover contribution between variable i and the other variables in the system, the net total directional connectedness of variable i is defined as

$$C_i^H = C_{.\leftarrow i}^H - C_{i\leftarrow .}^H \tag{9}$$

Finally, in order to measure the total spillovers in the system, the total connectedness for the system is constructed as

$$C^H = \frac{1}{N} \sum_{i,j=1, i/=j}^{N} \tilde{\theta}_{ij}^H , \ t = 1, \ldots, T \tag{10}$$

3. Data and empirical results

3.1. Data

Soybeans futures, gold futures, and WTI Light Sweet Crude Oil futures data from the Chicago Mercantile Exchange (CME) are used to

represent agricultural, metal, and energy products for comparative analysis, respectively, which is dictated by the availability of high-frequency data for commodities. Although we only obtained high-frequency data for three commodities, these three commodities are the most typical commodities. All high-frequency data for commodity markets is collected from the Datastream database.

With the development of commodity financialization, the volatility of commodities is more vulnerable to news-based factors rather than fundamental factors. In this paper, realized volatility of commodities is calculated based on high frequency data, which are more sensitive to macro news related factors. Thus six factors are selected from macro-economics and capital markets to a broader geopolitical dimension which can capture the different responses of commodity volatility to the changes of these factors. According to existing literature, six macro factors are chosen including economic policy uncertainty (EPU; Balcilar et al., 2016; Bilgin et al., 2018), the economic surprise index (ESI; Maveé et al., 2016), default spread (DEF; Bhardwaj et al., 2015; Ordu et al., 2018), the investor sentiment index (SI; Bahloul, 2018; Ji et al., 2020b), the volatility index (VIX; Silvennoinen and Thorp, 2013; Bilgin et al., 2018), and the geopolitical risk index (GPR; Antonakakis et al., 2017; Plakandaras et al., 2019). They are from three dimensions, namely, macroeconomics, capital market, and geopolitical risk. Details on these six macro information indicators are given in Table 1.

Given the availability of high-frequency historical data, our sample starts from January 9, 2012 and ends on December 19, 2016. According to the high-frequency data applications of commodities by Haugom et al. (2014) and Luo et al. (2019), we believe that 5-year high-frequency data is sufficient to characterize the realized volatility of commodities. Since futures are not continuously traded, we exclude all data on soybeans futures trading between 13:15 CST on Friday and 20:30 CST on Sunday as well as all data on gold and crude oil futures trading between 17:15 EST on Friday and Sunday 18:00 EST on Sunday, following Andersen et al. (2001, 2003, 2007). Moreover, we define the daily trading hours of soybeans futures and gold/crude oil futures on a certain day as the period from 20:30 CST and 18:00 EST of the previous day to 13:15 CST and 17:15 EST that day, respectively. In addition, we also exclude any data from inactive trading days and certain holidays, such as Christmas, Thanksgiving, etc. Finally, as the data frequency of the investor sentiment index is weekly, we replace the realized volatility of the commodities with weekly data, which consisted of 204, 230, and 230 observations for soybeans, gold, and crude oil futures, respectively.

Table 2 reports the descriptive statistics of the realized volatility of the commodity futures and macro factors. Panel A of Table 2 shows that the mean values of the realized volatility of the three commodity futures are around 0.018, of which gold is the largest, and soybeans is the smallest. However, based on the median, the realized volatility of gold futures has the smallest median value of 0.010, while the realized volatility of crude oil futures has the largest median value of 0.015. This means that the intraday returns of gold futures are more stable, and the intraday returns of crude oil has higher uncertainty most of the time. In addition, the realized volatility of the three commodity futures shows positive skewness, excess kurtosis, and fat tails, and the realized volatility of soybeans futures has the largest skewness and kurtosis. The results in the last three columns indicate that the realized volatility series of all the commodity futures significantly differ from the normal distribution; these variables are all stationary.

Panel B of Table 2 presents the statistical characteristics of the first difference of the macro information indicators.[1] The results show that the mean of GPR is the largest, its positive value indicates an upward trend of global geopolitical risk. GPR has the largest range and volatility,

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[1] Since the statistical characteristics of the macro information indicators in the three subsamples are similar, this paper only lists the statistical characteristics of the macro information indicators in the subsample containing gold futures data.

Table 1
Description of macro information indicators.

	Indicator	Definition/Formula	Data sources
Macroeconomics	US Economic Policy Uncertainty Index (EPU)	US Economic Policy Uncertainty Index, proposed by Baker et al. (2016), is a policy-related economic uncertainty index based on the frequency of newspaper reports.	Bloomberg Database
	Citi Economic Surprise Index (ESI)	Citi Economic Surprise Index measures the difference between the actual data and the consensus forecasts. A positive value means that the actual economic condition is better than the consensual expectation, and a negative value means that the actual economic condition is worse than expected.	Bloomberg Database
	Default Spread (DEF)	Default Spread is used to capture the business cycle component. Default Spread = Moody's Seasoned Baa Corporate Bond Yield (BAA) - Moody's Seasoned Aaa Corporate Bond Yield (AAA)	Bloomberg Database
Capital Market	Investor Sentiment Index (SI)	The Investor Sentiment Index, proposed by Bahloul (2018), is constructed by the data from the CFTC DCOT reports. It is used to measure investors' beliefs regarding future asset prices and risks, reflecting their level of optimism or pessimism about the market.	Commodity Futures Trading Commission (CFTC) Disaggregated Commitments of Traders (DCOT) Report
	Volatility Index(VIX)	The Volatility Index is the expectation of implied volatility in the prices of options. A higher value indicates that market participants expect the stock market to fluctuate more violently, reflecting the uneasy mood of market participants; on the contrary, a lower value represents that market participants expect the stock	Bloomberg Database

(continued on next page)

Table 1 (*continued*)

	Indicator	Definition/Formula	Data sources
Geopolitical Risk	Geopolitical Risk Index (GPR)	market to fluctuate moderately. The Geopolitical Risk Index, proposed by Caldara and Iacoviello (2018), counts the occurrence of words related to geopolitical tensions in 11 leading international newspapers.	https://www2.bc.edu/matteo-iacoviello/gpr.htm

Table 2
Descriptive statistics.

Panel A Realized volatility of commodity futures										
	Obs	Mean	Median	Max	Min	SD	Skew	Kurt	JB-test	DF-test	LBQ-test
Soybeans	204	0.016	0.013	0.074	0.006	0.009	3.414	19.027	0.001	0.001	0.055
Gold	230	0.019	0.010	0.173	0.004	0.022	3.384	17.341	0.001	0.001	0.000
WTI	230	0.018	0.015	0.090	0.006	0.011	2.367	13.056	0.001	0.001	0.000
Panel B Macro factors										
	Obs	Mean	Median	Max	Min	SD	Skew	Kurt	JB-test	DF-test	LBQ-test
EPU	230	−0.626	−5.285	191.320	−169.080	53.440	0.348	4.346	0.002	0.001	0.000
ESI	230	−0.218	−0.300	44.500	−36.400	11.778	0.204	4.093	0.008	0.001	0.007
DEF	230	−0.002	0.000	0.090	−0.170	0.038	−0.666	5.296	0.001	0.001	0.075
SI	230	0.001	0.000	0.502	−0.498	0.131	−0.201	5.774	0.001	0.001	0.001
VIX	230	−0.057	−0.155	27.720	−12.310	3.258	2.400	25.826	0.001	0.001	0.000
GPR	230	0.266	−2.332	527.828	−291.347	79.808	0.963	11.367	0.001	0.001	0.000

Note: SI = investor sentiment index, VIX = volatility index, DEF = default spread, EPU = US economic policy uncertainty Index, ESI = Citi economic surprise index, GPR = geopolitical risk index. All these variables are in first difference. For the Jarque-Bera tests, the Dickey-Fuller tests, and the Ljung-Box Q tests, the p-values are reported.

commodity markets exhibit persistent co-movements beyond the explanation of fundamentals. This excess co-movement is often due to the extensive flow of speculative investments across different markets (Le Pen and Sévi, 2018).

Despite the similarity of systemic connectedness in these three systems, there are clear differences in the information spillovers from the systems to each commodities. Soybeans for example, can gain 14.3% of information from the macro factors, whereas the number for gold is only 11.6%. Crude oil futures behave even more differently as its variation gains over 32.8% from the system. In other words, variations in the crude oil futures are much more sensitive to macro factors relative to other commodities.

Moreover, the spillover effects from each macro information indicator to commodity volatility are also significantly different in three commodity-macro information systems. In the soybeans-macro information system, the default spread has the largest explanatory power to

followed by EPU. Moreover, similar to the realized volatility of commodity futures, all series significantly differ from the normal distribution but all stationary.

3.2. Empirical results and analysis

The network approach proposed by Diebold and Yilmaz (2014) will be used to construct three information spillover networks between the macro information factors and soybeans, gold, and crude oil futures. Following Diebold and Yilmaz (2012), this paper constructs generalized variance decomposition matrices using the VAR(4) model and a 10-step ahead generalized forecast error variance decomposition.

3.2.1. Static analysis

In this section, we use the full sample to study the information spillover networks between commodity markets and macro information, and the results are shown in Table 3. From the table, we can see that the total connectedness between the realized volatility of the three commodities and the macro information indicators are quite similar. The system of crude oil futures and macro information has the largest systemic spillover effect (14.9%), followed by the system of soybeans futures and macro information, with total connectedness of 13.1%; the spillover effect of the system of gold futures and macro information is the smallest (12.6%). It is interesting to see that the contribution of each commodity market to the system are also very similar ranging from 11.7% for gold to 12.9% for soybeans. For the whole sample period, the similarity found here, to some extent, verifies the long-term co-movement occurring among commodity markets. This finding is consistent with Pindyck and Rotemberg (1990) and Fernandez (2015) that

soybeans volatility, explaining 4.3% of the variations in soybean RV. The second contributor is the investor sentiment index, with an explanatory power of 2.7%. In the gold-macro information system, VIX and SI has the top two factors in terms of explanatory power to gold volatility, contributing to 4.2% and 2.5% of its variations. The strong information gains for crude oil futures from the system are due to VIX. The volatility index explains 21.7% of crude oil futures' RV variations alone.

If we come back to the concept that the first three factors (EPU, ESI and DEF) are macroeconomic factors, a clear pattern can be found through comparing these systems. For soybeans, macroeconomic factors take the leading role. Whereas for gold and crude oil, financial factors take over that position. This is especially obvious for crude oil when VIX contributes over one fifth of the variations. The findings here are consistent with Zhang (2017) that crude oil has shown stronger characteristics of financialization in recent years and its price movements are more affected by the conditions in financial markets.

In addition, the results show that these commodities do not contribute much additional information to the system. Only gold futures are a net information transmitter, and its net contribution power is less than 1%; whereas soybeans and crude oil futures are net information receivers. Meanwhile, the net information gain for soybeans is only 1.5%. The situation is much different for crude oil as it has a much larger net gain (20.9%) from the system. This result supports that the crude oil market is more sensitive to changes in external information, and thus should be treated very differently in commodity markets.

Finally, a comparative analysis of the contribution of the different macro information indicators in the system reveals that the volatility index is the largest information receiver in each system from the

Table 3
Full-sample connectedness matrix.

Panel A:Soybeans

	Soybeans	EPU	ESI	DEF	SI	VIX	GPR	From
Soybeans	0.857	0.023	0.018	0.043	0.027	0.018	0.015	0.143
EPU	0.034	0.864	0.001	0.023	0.034	0.031	0.013	0.136
ESI	0.025	0.028	0.887	0.020	0.018	0.014	0.008	0.113
DEF	0.014	0.002	0.013	0.875	0.028	0.032	0.036	0.125
SI	0.036	0.034	0.030	0.027	0.862	0.002	0.010	0.138
VIX	0.009	0.068	0.009	0.020	0.031	0.834	0.029	0.166
GPR	0.011	0.021	0.010	0.012	0.010	0.034	0.902	0.098
To	0.129	0.175	0.080	0.145	0.148	0.132	0.111	Total
Net	−0.015	0.039	−0.033	0.020	0.009	−0.034	0.013	0.131

Panel B:Gold

	Gold	EPU	ESI	DEF	SI	VIX	GPR	From
Gold	0.884	0.018	0.010	0.010	0.025	0.042	0.012	0.116
EPU	0.014	0.877	0.005	0.013	0.029	0.043	0.019	0.123
ESI	0.004	0.022	0.922	0.012	0.017	0.011	0.011	0.078
DEF	0.010	0.006	0.025	0.849	0.051	0.044	0.015	0.151
SI	0.025	0.008	0.007	0.020	0.901	0.019	0.020	0.099
VIX	0.049	0.072	0.007	0.033	0.017	0.788	0.035	0.212
GPR	0.014	0.005	0.015	0.009	0.052	0.009	0.895	0.105
To	0.117	0.130	0.070	0.097	0.191	0.168	0.112	Total
Net	0.001	0.006	−0.008	−0.054	0.092	−0.044	0.007	0.126

Panel C:Crude oil

	WTI	EPU	ESI	DEF	SI	VIX	GPR	From
WTI	0.672	0.027	0.024	0.050	0.008	0.217	0.002	0.328
EPU	0.008	0.899	0.007	0.009	0.011	0.035	0.030	0.101
ESI	0.028	0.020	0.889	0.010	0.028	0.013	0.013	0.111
DEF	0.022	0.011	0.029	0.851	0.023	0.048	0.016	0.149
SI	0.013	0.006	0.014	0.025	0.911	0.022	0.009	0.089
VIX	0.041	0.065	0.007	0.036	0.030	0.792	0.029	0.208
GPR	0.005	0.012	0.011	0.011	0.015	0.006	0.941	0.059
To	0.119	0.141	0.092	0.140	0.114	0.340	0.099	Total
Net	−0.209	0.041	−0.019	−0.009	0.025	0.132	0.039	0.149

Note: SI = investor sentiment index, VIX = volatility index, DEF = default spread, EPU = US economic policy uncertainty Index, ESI = Citi economic surprise index, GPR = geopolitical risk index.

perspective of information inflow, with values ranging from 16.6% to 21.2%. From the perspective of information outflow, although there is no single largest information transmitter in the three systems, the economic policy uncertainty index is ranking the top three information transmitter of the six macro information indicators. In other words, the volatility index is most affected by changes in the system, while economic policy uncertainty is an important factor for system volatility. In terms of net contribution of the macro information to the system, the economic policy uncertainty index, investor sentiment index, and geopolitical risk index are net information transmitters for all systems, while the economic surprise index is a net information receiver for all systems. In addition, the results also show that the volatility index exhibits different performances in different systems. Specifically, it is a net information receiver in soybeans- and gold-macro information index systems, but a net information transmitter in crude-macro information index systems. This is because crude oil futures are more sensitive to changes in the panic index than soybeans and gold futures.

The net pairwise directional connectedness of the commodity-macro information systems can be visualized in a network such as (Diebold and Yilmaz, 2014), which can provide a much clear view of how each system are connected. Fig. 1 uses a coloured chord graph for this purpose. In the graph, coloured bands represent the net information flow between different indicators, and the larger width of the bands represents a higher level of net information flow. As can be seen in Fig. 1, the total level of net information flow between the crude oil futures and the system is the largest, followed by soybeans and gold. In the soybeans-macro information system, the default spread, volatility index, and geopolitical risk index are net information transmitters of soybeans volatility. In contrast, the economic policy uncertainty index, economic surprise index, and investor sentiment index are net information

receivers, where the default spread and soybeans volatility have the largest differences in their mutual explanatory power. Unlike the gold-macro information system, the share of the total level of the net pairwise directional connectedness between crude oil and each macro information indicator accounts for a quarter of the total level of the net pairwise directional connectedness in the system, especially the net information flow from the volatility index to crude oil volatility, which is the most noticeable net information flow.

3.2.2. Dynamic analysis

The static analysis of full-sample connectedness provides a good description of the connectedness between commodity futures volatility and macro information indicators throughout the full sample period, but the situation may change over time. In order to analyze the dynamic influence of each macro information index on the volatility of commodity futures, we construct dynamic connectedness networks of commodity-macro information systems using rolling estimation with a 50-week (nearly one year) window.[2]

Fig. 2 show the total connectedness in the commodity-macro information system, and the red dashed line in the figure shows the mean value of the dynamic total connectedness of each commodity-macro information system. As a whole, the mean value of the dynamic total connectedness of each system is about 60%, which reveals that there is a high degree of integration between the volatility of the commodity market and macro information in the short term. The range of the total

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[2] We also use 60, 70 and 80 weeks as three alternative window size, and the results are robust. Hence, we only present the results of the window size of 50 weeks.
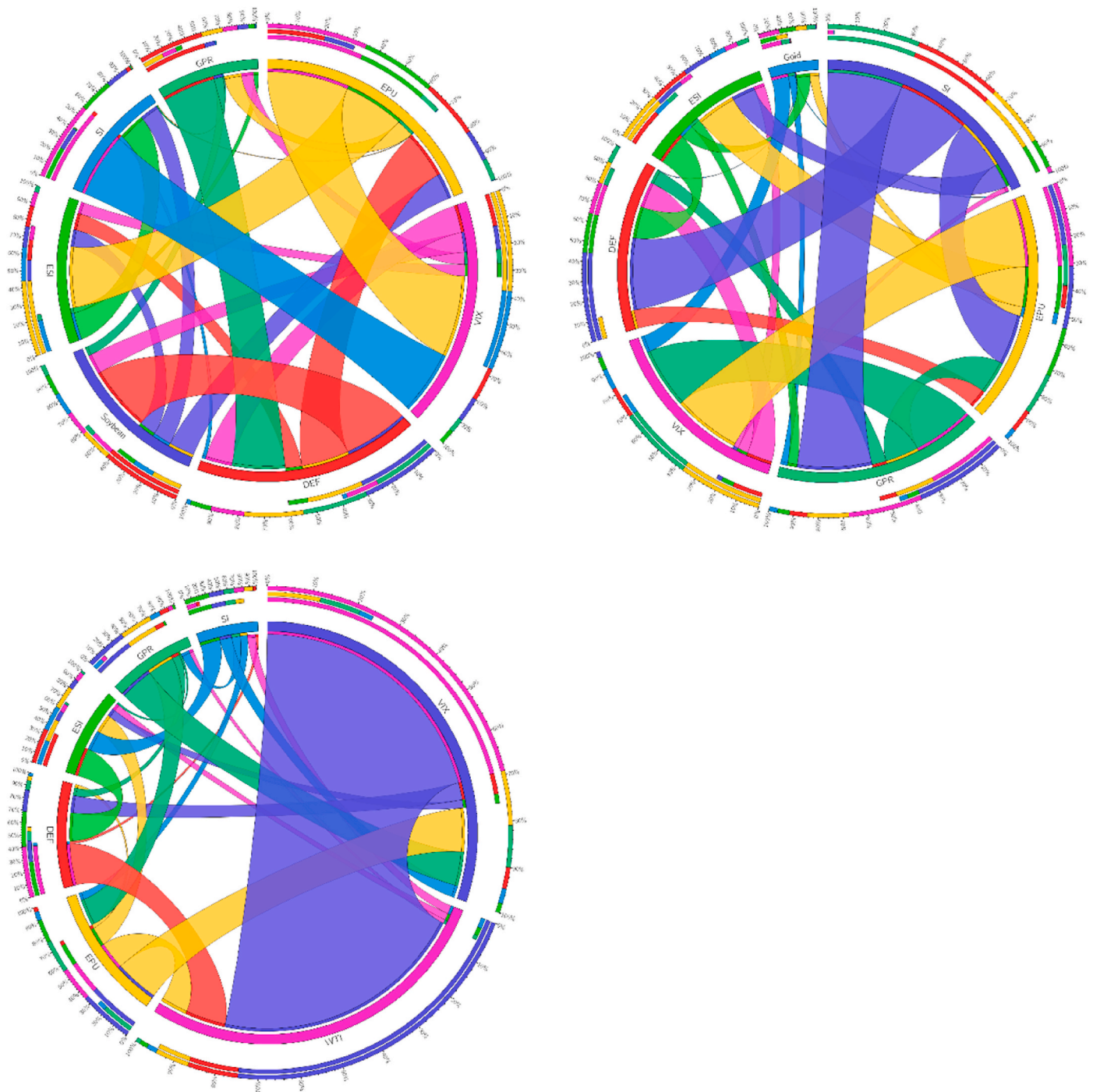
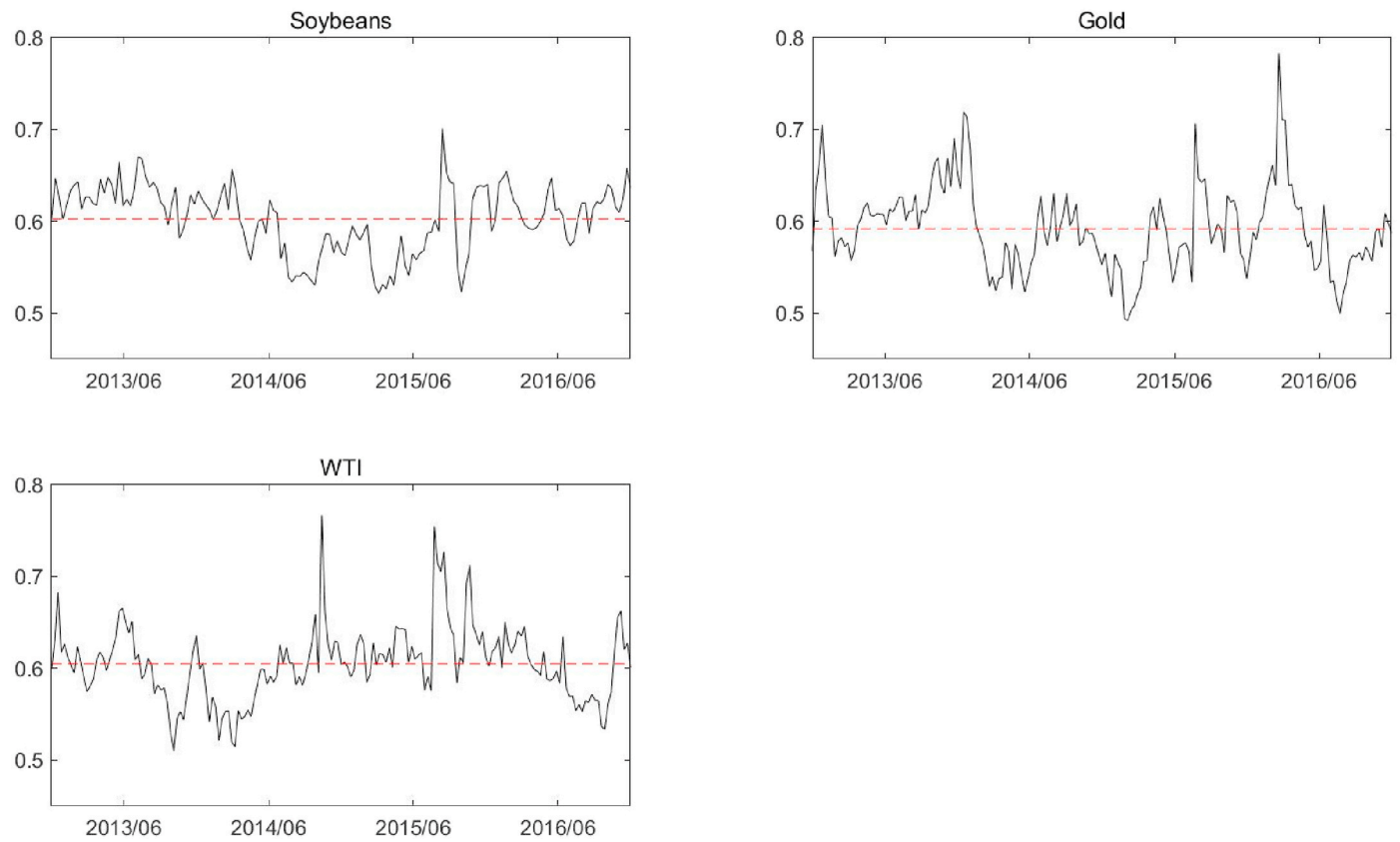**Fig. 1.** Commodity-macro information net directional connectedness networks.

Fig. 2. Dynamic total connectedness in the commodity-macro information systems.
(Note: The window size is 50 weeks. The horizontal axis shows the end time of each rolling window, and the red dashed line is the mean of the dynamic total connectedness)

connectedness of the soybeans-macro information system is concentrated between 50% and 70%, while the range of the total connectedness of the gold- and crude oil-macro information systems are relatively large, ranging from 47% to 78%. This indicates that the total connectedness of the gold- and crude oil-macro information systems have stronger time-varying characteristics. In particular, the total connectedness of the soybeans- and gold -macro information systems can be divided into three periods. The first corresponds to the beginning of the sample and extends from the beginning of 2012 to early 2014, in which the total connectedness was at a high level. From 2012, in response to the global economic downturn, a series of policy actions, such as quantitative easing, have been used across the world. These policies had a positive impact on the markets, but also increased the linkage between macro information and the commodity markets. The second focuses on the period that extends from early 2014 to around August 2015. Similar to Antonakakis et al. (2014) who find that the spillover effects of macro information decreases as the economy recovers, the total connectedness declined slightly during this period. The last period corresponds to the 2015–2016 global economic downturn and covers around August 2015 to the end of 2016. During this period, the total connectedness increased and reached a peak around August 2015. This peak can be explained by investor panic caused by the US stock market's plunge on August 24, 2015.

Fig. 3 presents the dynamic net total directional connectedness of commodity futures. In most periods, the dynamic net total directional connectedness of commodity futures is between −30% and 30%, the change of the explanatory power of gold and crude oil futures to the system is much higher than that of soybeans to the system. In addition, similar to the static connectedness networks, gold futures play a dominant role in the information transmissions, while soybeans and crude oil futures are net information receivers.

Furthermore, combining Figs. 2 and 3, we find that in most periods, the change of the dynamic total connectedness is not caused by the net information flow from commodity futures to the systems. The only exception is the significant increase in the total connectedness in the crude oil-macro information system at the end of 2014, which is caused by the substantial increase in the information outflow from crude oil futures. Next, we examine the information outflow from macro information to commodity futures volatility. Fig. 4 plots the corresponding results, where Table 4 reports the ranking of the information spillover effects of macro information indicators to commodity futures. In terms of the information spillover effects of macro information to soybeans, the total effects are between 40% and 80%, and the overall trend is similar to changes in total connectedness, showing a U-shape. Moreover, changes in the influence of each macro information on soybeans volatility is relatively small, where the default spread and the investor sentiment index account for a relatively large proportion. For gold futures, the fluctuation of the information inflow mainly stems from the investor sentiment index and the volatility index. Together, the mean of the information outflow from the investor sentiment index and the volatility index are about 11%. For crude oil futures, the prices fluctuation mainly stems from the default spread and the volatility index. In other words, the business cycle and the investors panic are the main risk sources for crude oil futures volatility. Moreover, in the short term, the volatility of crude oil futures is more affected by geopolitical risk than gold futures. It is worth noting that when the total connectedness and the net directional connectedness increased significantly at the end of 2014, the information outflow from macro information to crude oil volatility did not significantly increase. This finding confirms Maghyereh et al. (2016) who claim the fall in crude oil prices in 2014 was not caused by an increase in information inflow from external information to crude oil, but rather by an increase in the production of shale oils. In other words, it is driven by the fundamentals of crude oil, or the oversupply in the global market. In addition, the increase in information outflow from the volatility index to each commodity futures volatility in August 2015 also confirms that the investor panic caused by

the US stock market's plunge is responsible for the sudden increase in the total connectedness.

4. Conclusion

Taking soybeans, gold and crude oil futures as representatives of three main types of commodities in the international market, we study how macro factors affect their price fluctuations. Extended from the existing literature, we consider three dimensions of macro factors, namely, macroeconomics, capital market and geopolitical risks in a systemic framework to evaluate their interactions with each commodities. We also use high-frequency data to calculate realized volatility for each commodity and the Diebold and Yilmaz (2014) approach to evaluate both static and dynamic connectedness.

The empirical results show certain similarities in three networks (one for each commodity), which is consistent with the strong co-movement among commodities found in the existing literature. There are however, some clear differences. First, the role of each commodities in their own networks differs: gold plays a dominant role in its network and is a net information contributor, whereas soybeans and crude oil futures are net information receivers. Second, crude oil futures volatility is more sensitive to changes in macro information than soybeans and gold futures. In particular, investor panic has the greatest impact on the realized volatility of crude oil and gold futures, while the business cycle contributes the most to the realized volatility of soybeans futures. Third, our results show that the volatility index is the largest information receiver in each system, while economic policy uncertainty is an important source for systemic volatility.

Interestingly, the total connectedness of the gold- and crude oil-macro information systems present significant time-varying characteristics, while the total connectedness of the soybeans-macro information systems is relatively stable. It reflects that gold and crude oil are special in the sense of dynamic process.

There are also some interesting differences for each commodity. The main driving forces for each time varying total network connectedness differ across commodities. In particular, the fluctuation in the total connectedness in the soybeans-macro information system mainly stems from default spread and the investor sentiment index, while the fluctuation in the total connectedness in the gold-macro information system mainly stems from the investor sentiment index and the volatility index. Additionally, the fluctuation in the total connectedness in the crude oil-macro information system mainly stems from default spread and the volatility index. Moreover, geopolitical risk is also an important influence factor on the information spillover of the crude oil-macro information system.

The abovementioned empirical results provide useful information for both investors and policymakers. They should focus on the impact of macro factors on commodity markets when preventing and controlling commodity market risks, especially in the short-term trading of commodity futures. Specifically, market regulators should strengthen the monitoring of speculation in the financial and commodity markets and stabilize investor sentiment in the capital markets. Specific regulatory measures should be applied to different commodity types in order to achieve the optimal regulatory effects. Investors can also diversify their investment portfolios according to the different characteristics of information spillovers between commodity futures and macro factors, so as to minimize the risk of their investment. For example, in addition to paying attention to the impact of market sentiment on all commodity markets, the impact of business cycles on soybean and crude oil price fluctuations and the impact of geopolitical risk on crude oil price fluctuations should be specifically considered. More importantly, investors and market regulators should dynamically adjust investment portfolios or commodity market management strategies in response to changes in the correlation between commodity markets and macro factors over time.

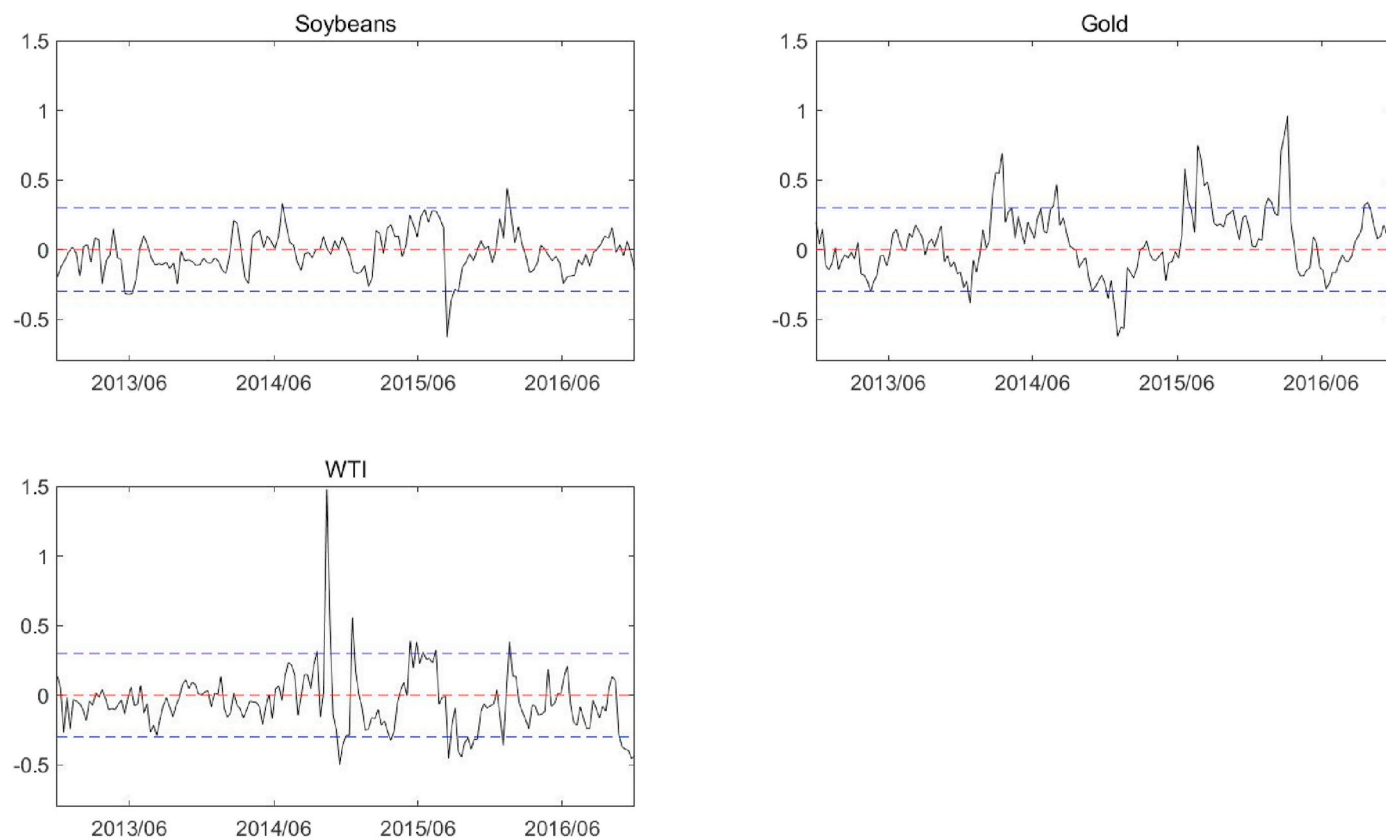While this paper shows some interesting implications that macro-

Fig. 3. Dynamic net total directional connectedness of commodity futures.
(Note: The window size is 50 weeks. The horizontal axis shows the end time of each rolling window, and the red and blue dashed line are 0 and ± 30%, respectively)
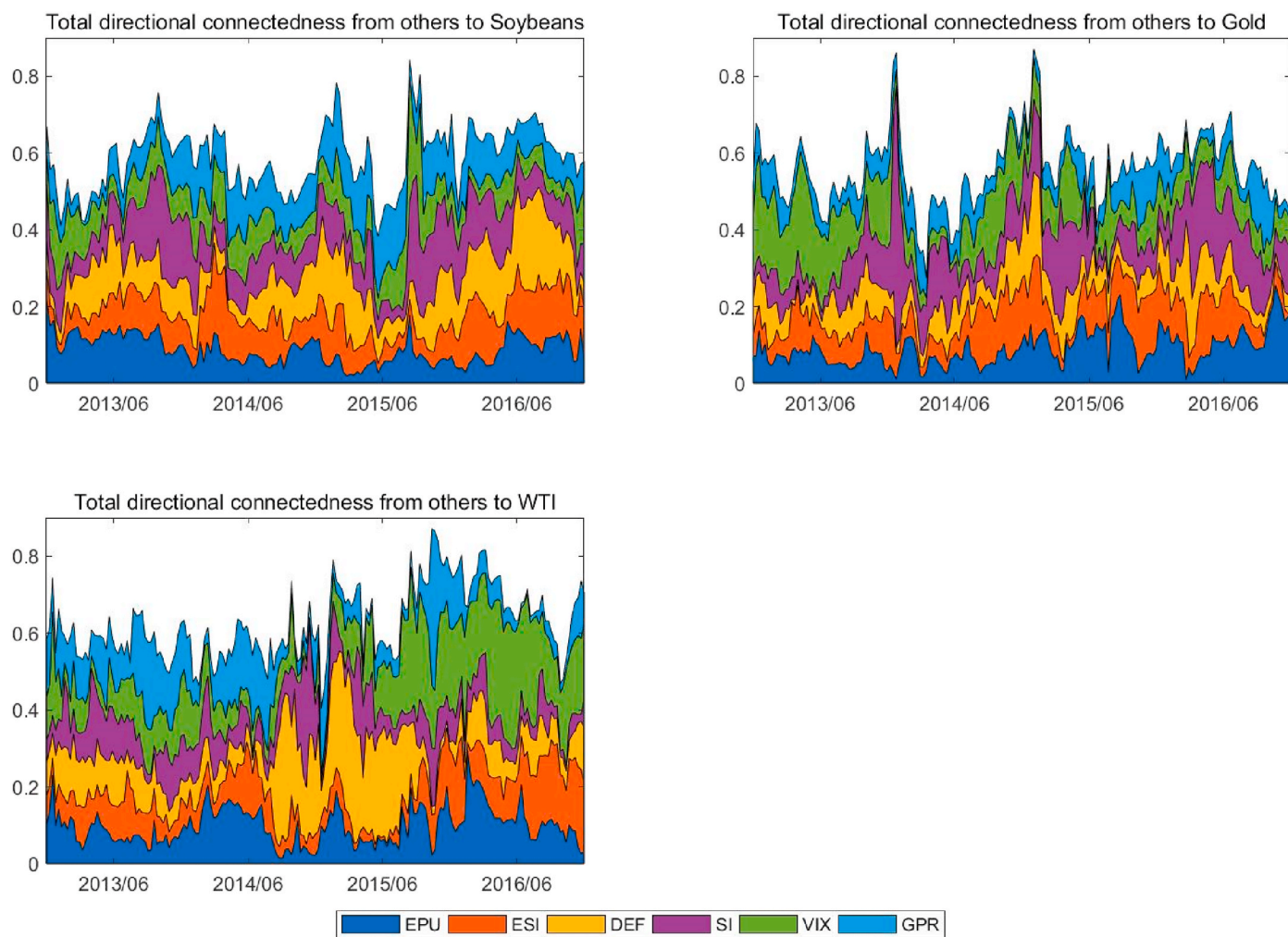
Fig. 4. Dynamic pairwise directional connectedness from macro information indicators to commodity futures.
(Note: The window size is 50 weeks, and the horizontal axis shows the end time of each rolling window)

Table 4
Ranking of the information spillover effects of the macro information indicators on commodity futures.

Rank	Soybeans		Gold		WTI	
	Transmitter	Mean	Transmitter	Mean	Transmitter	Mean
1	DEF	0.113	SI	0.118	VIX	0.138
2	SI	0.109	VIX	0.111	DEF	0.123
3	GPR	0.098	ESI	0.095	EPU	0.098
4	ESI	0.095	EPU	0.093	GPR	0.095
5	EPU	0.088	DEF	0.077	ESI	0.089
6	VIX	0.083	GPR	0.066	SI	0.083

factors can play very critical roles in commodity markets, it is important to note the fundamental reasons remain unclear and worth for further investigation. The time series approach used here can potentially combine with standard econometric analysis, which could be an interesting direction of future research.

CRediT authorship contribution statement

Min Hu: Software, Data curation, Writing - original draft. **Dayong Zhang:** Conceptualization, Writing - original draft, Writing - review & editing. **Qiang Ji:** Supervision, Writing - review & editing, Funding acquisition. **Lijian Wei:** Supervision, Writing - review & editing, Funding acquisition.

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